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QUANTITATIVE ASSESSMENT OF LONG WAVES
IN ECONOMIC DEVELOPMENT

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ABSTRACT

Spectral analysis and a new filtering technique are used to determine the existence of Kondratieff's cycles. This new methodology is briefly explained and should solve statistical problems related to the study of Economic fluctuations and particularly those related to the study of long cycles. The index of Industrial Production and the G.N.P. of the major industrialized countries are analyzed, as are other international series. The results support the empirical existence of the Kondratieff's cycle.

RÉSUMÉ

L'analyse spectrale et une nouvelle technique de filtrage sont utilisées pour vérifier l'existence des cycles Kondratieff. Cette nouvelle méthodologie, qui est brièvement exposée, devrait permettre de résoudre certains problèmes statistiques reliés à l'étude des fluctuations économiques et particulièrement à celle des cycles de longue durée. L'indice de la production industrielle et le P.N.B. des principaux pays industrialisés ainsi que des séries internationales sont analysés. Les résultats supportent l'hypothèse de l'existence empirique des cycles Kondratieff.

1. INTRODUCTION¹

With the ongoing slow growth in capitalist economies since the early 1970's and the failure of short-term economic policies economists have changed the emphasis of their work. They are now more concerned in general about the long-term factors affecting economic growth such as technological and demographic changes. They are also continuing their search for a more dynamic theory of economic growth as an alternative to the mainly static neoclassical-Keynesian framework. These events have set the stage for a renewed interest in the long-wave theory.² This 40- to 60-year business cycle has been named the Kondratieff, after N. Kondratieff³ one of the pioneers of the long-wave theory.

Many theories have been developed to explain the recurrence of periods of faster rates of growth followed by slower rates and even depression. Table 1 shows some possible explanations of the Kondratieff cycle.

The efforts to explain the mechanisms generating the Kondratieffs would be more valuable if its existence were more generally recognized; but the various studies that have tried to demonstrate its empirical existence have produced conflicting results. In fact, most economists are sceptical

¹This paper is a summary of my Masters Thesis presented at Université de Moncton, Gervais [1986]. Therefore the opinions expressed in this study are those of the author and do not represent those of Statistics Canada. I would like to thank MM. Darryl Rhoades for his important contribution and Lyle Sager for his comments.

²Business Cycles in Canada, by the late Senator Maurice Lamontagne reflects the interest here in Canada.

³See a recent translation of his works, Kondratieff [1984].

TABLE 1

SOME THEORIES OF THE KONDRATIEFF CYCLE

MAIN CAUSE	AUTHORS
Major innovations	Schumpeter [1964], Mensch [1979]
Lagged adjustments in the capital production sector	Forrester [1977]
Lagged adjustments in the primary sector production	Rostow [1978]

that a long-wave cycle exists. Many of the authors¹ who developed theories of the long-wave cycle have provided "historical facts" that appear to fit the hypothesis. Of course, those "facts" can be attributed to other factors. Systematic studies based on historical economic time series are fewer, but have produced a wide range of different results. At one end of this spectrum, van Duijn [1983: 158] came to the conclusion that "...long-wave growth is an adequate typification of the development pattern during the past century." Imbert [1959], and Broersma [1978]² shared the same conclusion. At the other end, van Ewijk [1981: 365] concludes: "Although the process of long-term economic growth is far from steady, the long movements do not correspond to the long-wave pattern." Although Kuczynski [1978] found evidence in favour of the long wave, he was sceptical about

¹Schumpeter [1964], Rostow [1978] and Lamontagne [1984] are good examples.

²Broersma's doctoral dissertation written in Dutch is reviewed by van Duijn [1979].

his conclusions. Haustein and Neuwirth [1982] found no evidence of the Kondratieffs in the individual series but their interrelationship seemed to support the hypothesis. Bossier and Huqé's [1981] results for Belgium were inconclusive.

The purpose of this paper is first to identify the reasons why these results differ and second, to present a new methodology that forms the basis of the results presented in section 4.

Before addressing these topics, we will summarize the main empirical characteristics of long-wave cycles:

1. They are mainly an international phenomenon. At the national level, the cycles can be mixed with the country's own internal dynamic development;
2. They manifest themselves in
 - (a) aggregate economic time series such as GNP and industrial production
 - (b) changes in primary sector prices relative to secondary sector prices
 - (c) the debt burden of economic agents
 - (d) social and demographic changes;
3. The duration and the amplitude of the Kondratieff cycles vary;
4. The upward phase might differ from the downward phase in terms of amplitude and duration;
5. Business cycles have a long upward phase and a short downward phase during the Kondratieff upswing and vice versa for the downswing. The Kondratieffs are influenced in the same way by longer-term movements, sometimes referred to as the secular trend.

The present research concentrates on the behaviour of real macro-economic variables. We test whether the long-wave cycle is a proper characterization of economic development in general and not whether it is sector specific.

2. TESTING THE LONG-WAVE CYCLE HYPOTHESIS

In this section, we demonstrate that conflicting results can be mainly attributed to differences in methodology. While the choice of alternative data series has undoubtedly contributed to this conflict, we argue that the weaknesses of the methodologies employed render many previous test results questionable.

To test the long-wave hypothesis, three statistical problems must be solved:

- a) the data series must be detrended (first order stationarization);
- b) the detrended series must be stationarized to the second order;
- c) one must test for the existence of the Kondratieff cycle.

2.1 Stationarization

The first two problems relate to the statistical properties of most economic time series. They are characterized by an increasing trend or mean that has to be removed in order to study cycles. Moreover, the detrended data have an increasing variance because the amplitude of the business fluctuations depends on the level of economic activity. An increasing trend implies therefore a growing variance of the cycles.

Two approaches have typically been taken to detrend the data: (1) the estimation of a trend which is then subtracted from the raw data; (2) the elimination of the trend by differencing. Both of these approaches require an assumption about the functional form of the trend which is not known a priori.

Various studies¹, based on the first approach, assume simple deterministic functions of time which are linear or higher-order polynomials in time. There are theoretical as well as practical problems involved with this assumption. On the theoretical side, Reveridge and Nelson [1981:152] state:

"A rather unsatisfactory implication of this approach is that the long-run evolution of the time series is deterministic and therefore perfectly predictable. If in fact the changes in economic series are a random process in a statistical sense, then the deviation of the series from any deterministic path will grow without bound."

Moreover, Nelson and Kang [1981] and Chan et al [1977] demonstrated that the assumption of a deterministic trend, when the true trend is non-deterministic, causes spurious periodicity in the deviations from the assumed trend.

On the practical side, van Duijn [1983: 148] states: "Our experience is that the pattern of residuals is very sensitive to the (deterministic) trend assumption that is made." van Ewijk [1981] shared the same view.

¹See for example Kondratieff [1984], Kuczynski [1978], Haustein and Neuwirth [1982].

There is also a bias in the estimation of the parameters defining the trend in the research we surveyed. The error term, i.e. the difference between the actual data and the estimated trend contains the cycles. This error term might be autocorrelated and heteroscedastic as well. None of the tests used to identify Kondratieff cycles applied an estimator that takes into account autocorrelation. Moreover, the work of Bossier and Hugé [1981] provides an example of the situation where the variance of their series was not stationarized in order to avoid the problem of heteroscedasticity.

A logarithmic transformation of the data was used in other studies to render the error term homoscedastic. This transformation implies that the business cycle amplitude depends on the level of output. Trend and cycles are multiplicative and this model is commonly used. In fact, most production indices are seasonally adjusted on that assumption. Thus logarithmic transformation seems to be the proper way to stationarize the variance of a series when estimating the trend.

Turning to the second approach, we find that differencing is commonly used to stationarize the mean of a time series. This method assumes a non-deterministic trend, the current values of the trend depend on its past values. This is a reasonable assumption for economic time series. Moreover, variance non-stationarity can be solved by using a growth rate transformation such as the first difference of the logarithm or the usual percentage rate of growth.

The differencing method, adjusted or not for variance, is inadequate to test the Kondratieff hypothesis because this transformation eliminates

most of the amplitude of the 40-60 year cycles. The differencing method may be regarded as a filter.¹ From the filter point of view, first differences change the relative amplitude and position of the cycles of the input series. The distortion of amplitude for this filter is given in Figure 1 and Table 3. For example, the original amplitude of a 50-year cycle is multiplied by 0.13 while for a 2-year cycle, the original amplitude is multiplied by 2.0. In other words, only 13% of the amplitude of the Kondratieff cycle is still remaining after first differencing.² Differencing-type transformations are therefore not pertinent to the study of long cycles such as Kondratieffs. It is not surprising that studies based on this approach have rejected the empirical existence of the Kondratieff cycle (see van Ewijk [1982] and Bossier and Huq  [1981]).

To summarize, the deterministic approach to detrending the data is inadequate from a theoretical point of view, especially for identifying the Kondratieff cycle. The non-deterministic approach, filtering, may be an adequate alternative but the type of filter typically used severely distorts the frequencies at which Kondratieff cycles are normally thought to occur. The conclusions of the studies based on one or the other of the approaches to mean non-stationarity should be taken very cautiously. The multiplicative model seems to be a good specification of the increasing variance.

¹Difference equations may be used to represent filters; see equation (1), pg. 13.

²The distortion is the same if the percentage rate of growth is used (see Rhoades [1983]).

Figure 1

- 7a -

Amplitude distortion of first differencing

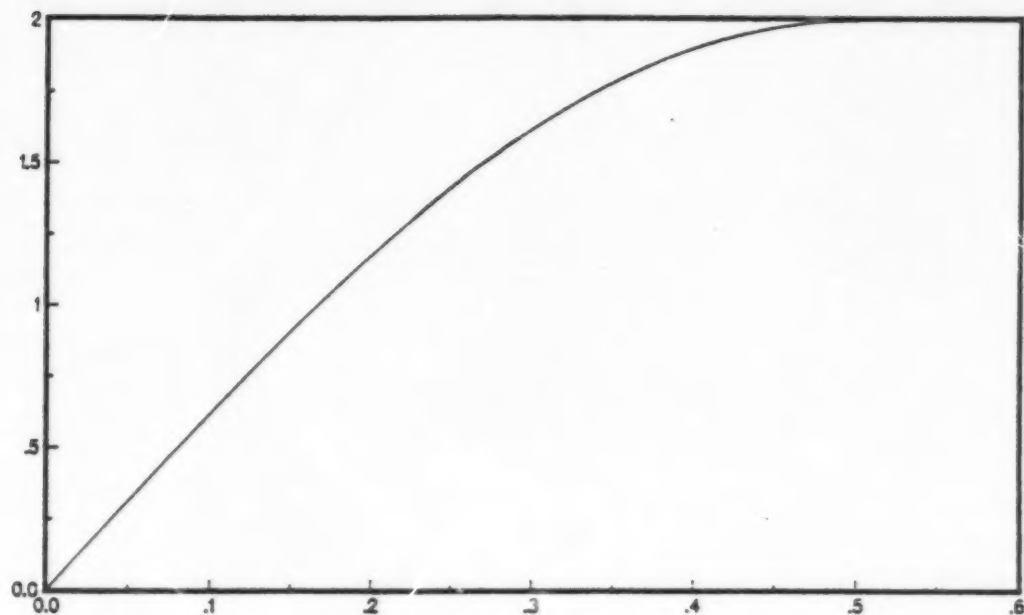
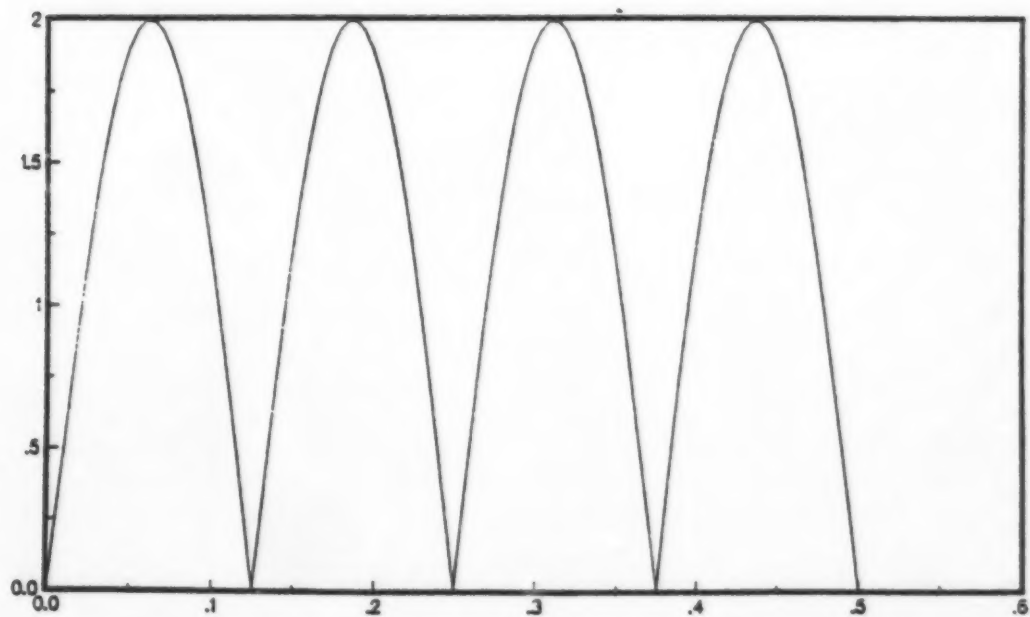


Figure 2

Amplitude distortion of ninth differencing



2.2 The Identification of Cycles

There are mainly two methods to identify business cycles: the turning point approach or the spectral analysis approach. The former requires a definition of a turning point; such definitions usually lack a general theoretical justification. In fact, different definitions lead to quite different results when the long-wave hypothesis is tested. van Duijn [1983: 147-164], using a set of major business cycle dates derived from one definition was unable to reject the long-wave hypothesis. However, van Ewijk [1981] using the same data series and the same general methodology as van Duijn¹ but a different turning point definition rejected it.

Spectral analysis of van Duijn's methodology can explain why the results are so sensitive to turning point selection. van Duijn computes the annual average growth rate between Juglar peaks (7-11 year business cycles). He tests if Juglar average growth rates are different during Kondratieff upturns than during their downturns; this being so, he takes it as indirect evidence that the Kondratieff exists. His measure of Juglar average growth rates can be approximated by a 9-year growth rate from which the Juglar peak values can be analyzed.

The amplitude distortion of the 9th difference (the 9-year growth rate), Figure 2, suggests that the filtered series reflects more cycles than just the Kondratieffs. This might explain why changes in turning point dating influence the results.

¹van Duijn's tests first published in Dutch in 1979 were translated into English in 1983.

To test the long-wave hypothesis based on turning point methodology, one would have to detrend the data and eliminate shorter fluctuations without altering the Kondratieff cycle. van Ewijk [1981] maintains that he used a method that meets these requirements. However, the numerous steps involved in defining the many turning points make it impossible to use spectral analysis to examine the properties of his method and to verify his results. In short, the results based on turning point methods will always be open to criticism because of the arbitrariness of the definitions upon which they are based.

Spectral analysis has important advantages for identifying business cycles: no arbitrary definition of turning points is needed; there is no need to eliminate shorter fluctuations.¹ The spectrum of a stationary time series gives information about all cycles contained in the series. Any time series can be represented as a summation of cosine waves:

$$X_t = \sum_{i=0}^{\infty} R_i \cos(2\pi f_i t + \theta_i)$$

where R_i is the amplitude of a cosine wave of frequency f_i (periodicity is $1/f_i$). θ_i represents the phase shift of that cosine wave relative to $\theta_i=0$. The spectrum of X_t , $\Gamma_{xx}(f)$, defines the amplitude of a series as a function of its frequency (f):

$$\Gamma_{xx}(f) = \frac{R^2(f)}{2}$$

¹Gottman [1981] gives a good introduction to spectral analysis.

This definition of the spectrum distributes the total variance of a series across a predefined set of frequencies (f). For example, Figure 3 shows the estimated spectrum of a series produced by cosine waves. It is defined for $0 \leq f \leq 0.5$. For $f = 0$, the periodicity is infinite, the longest cycle possible. For $f = 0.5$, the periodicity is 2, the shortest observable cycle. The spectrum shows that there are 2 cycles. Their periodicity is 50 and 25 periods respectively (periodicity (p) = $1/\text{frequency}$, $p = 1/0.02 = 50$ and $p = 1/0.04 = 25$). Their amplitude¹ is 5 (i.e. the square root of 12.5 times 2) and 3 (i.e. the square root of 4.5 times 2). The total variance of the series is 17; 73.5% of that is explained by the longest cycle.

Figure 4 illustrates another aspect of spectral analysis. The straight line in this figure is the spectrum of a white noise process. For these processes, all frequencies contribute equally to the total variance. By comparison, the dotted line in Figure 4 illustrates the spectrum for a series where most of the variance is explained by frequencies in the neighbourhood of 0.1 and which corresponds to a cycle of about 10 periods.

The spectrum is estimated only for a given set of frequencies, the Fourier frequencies. They are the multiples of a frequency whose periodicity is equal to the length of the data record ($1/p$, $2/p$, $3/p$, ... 0.5). Roughly speaking, the estimated spectrum, sometimes referred to as the periodogram, cannot represent cycles that are longer than the data record.

¹See page 9 for the relationship between the spectrum and the amplitude.

Figure 3
Spectrum of deterministic cycles

- 10a -

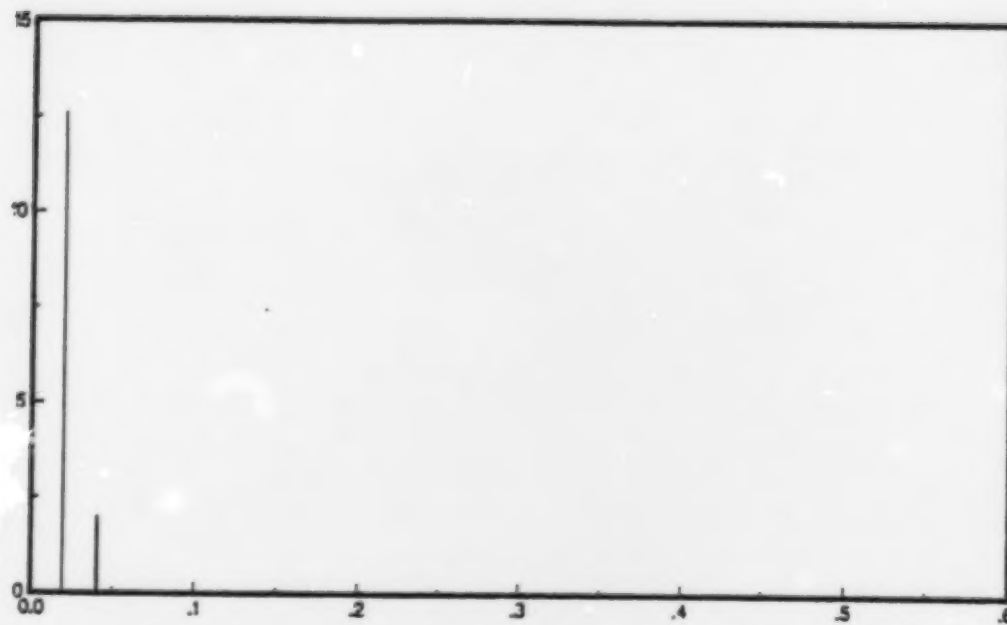
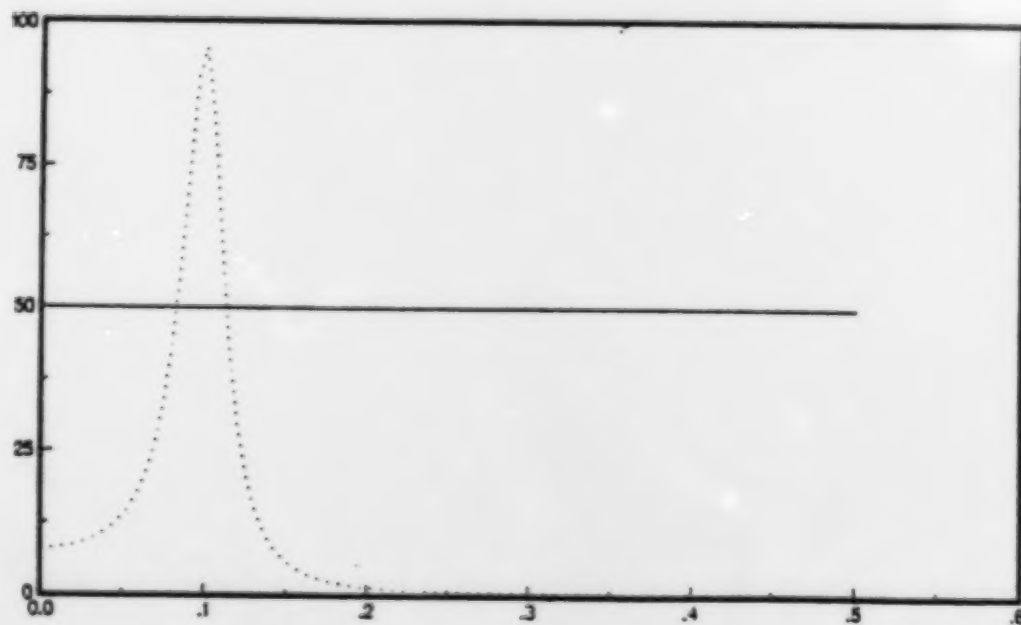


Figure 4
Spectrum of white noise process (straight line) and
of a 10 period non deterministic cycle (dotted line)



3. A NEW DETRENDING (FILTERING) METHOD

The discussion of the previous section suggested a number of criteria by which a detrending method should be judged. First the trend, however defined, must be non-deterministic. Second, the specification of the trend is not required a priori. Third, the Kondratieff's amplitude must be unaltered in the detrended data. As we will demonstrate spectral analysis appears to meet these criteria. However, there are other difficulties related to the application of this technique which include: starting values, trend discontinuity and outliers. The nature of these problems and the recently developed techniques to solve them will be outlined.

3.1 Spectral Analysis and the Mean Non-Stationarity

The spectrum decomposes a time series into cosine waves. A cycle corresponding to a particular wave reflects a particular periodicity and has associated with it a zero mean. Suppose we add to the first cycle another cycle corresponding to a different wave and reflecting a longer periodicity. Now the first cycle is going to fluctuate around the second cycle which will be regarded as the trend of the first cycle. From a spectral point of view, the trend of a given cycle is therefore composed of all cycles of longer periodicity and the question is how do we get rid of it. Roughly speaking, according to the framework given above, to detrend a time series, one has to eliminate all cycles whose periodicity is longer than the sample size.

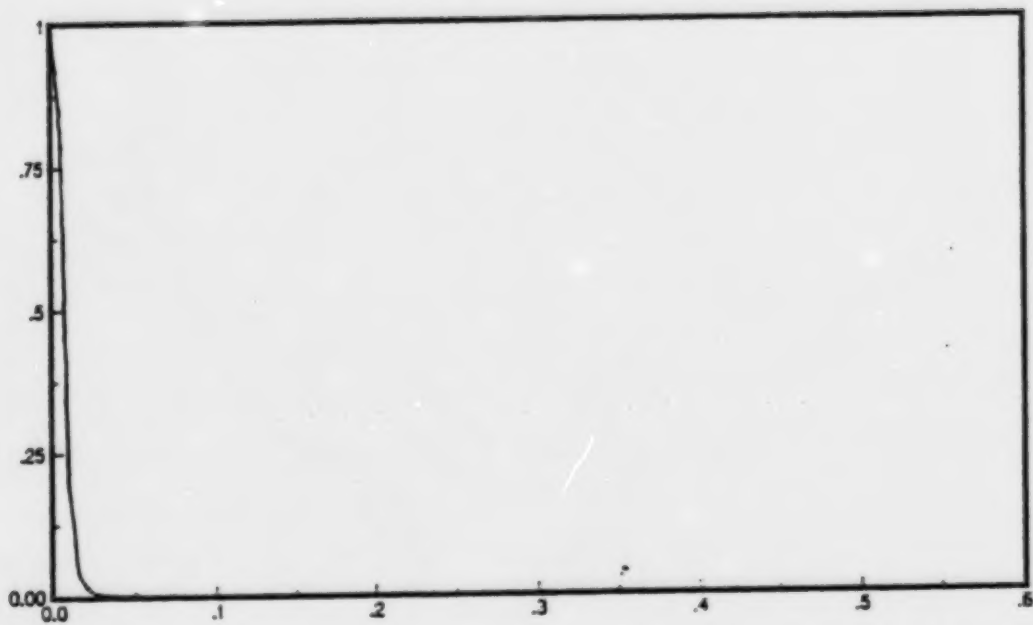
Spectral analysis permits us to design filters that can achieve this in two ways. Filters can eliminate those cycles directly or they can estimate the non-deterministic trend, which can be subtracted from the original series. Differencing is a common example of the first approach; Central Symmetric Moving Averages (CSMA) used in X-11 seasonal adjustment is an example of the second approach.

Even though filtering is a common detrending method, moving average (MA) representations of the filters are inadequate because they cannot be infinite in practice. For this reason, one cannot design a practical MA filter that estimates the trend-related movements while leaving the long-wave cycle unaltered.

On the other hand, autoregressive moving average filters (ARMA filters) are parsimonious representations of infinite MA filters. One can therefore design ARMA filters that estimate the trend and yet leave the Kondratieffs unaltered. Figure 5 illustrates the amplitude distortion of a simple ARMA filter that estimates such a trend. The filtered series which represents the estimated trend is composed only of cycles related to secular movements (100 years and longer). The deviations from this estimated trend contain only the unaltered shorter cycles including the Kondratieffs.

Notice that the functional form of the process generating the trend does not need to be known a priori. The only requirement is that the true trend can be represented as long cyclical waves (section 3.4 deals with the cases that do not meet this requirement).

Figure 5
Amplitude distortion of
trend filter applied bi-directionally



3.2 The Starting Value Problem and Its Solution For Uni-directional Filtering

The general form of an ARMA filter applied in one direction (uni-directional filtering) is:

$$\sum_{i=0}^m b_i Y_{t-i} = \sum_{j=0}^c a_j X_{t-j} \quad (1)$$

where $t = 1, 2, \dots, n$

X_t is the input data

Y_t is the filtered series

a_j and b_i are the MA and AR coefficients respectively.

Now the problem with applying this filter is that the autoregressive part, Y_t , depends on its past values and ultimately on its starting values which are unknown. Rhoades [1985] has developed a method that addresses this problem; its main features follow.

The methodology requires that we assume an initial set of starting values for the autoregressive part of the filter. If these assumed starting values differ from the true or correct values, a distortion, called a transient, will appear in the filtered series. We know the functional form of the transient which depends on the roots of the AR polynomial. It is,

$$T.S = \sum_{k=1}^p (A_k R_k^{-t} \cos \theta_k t + B_k R_k^{-t} \sin \theta_k t)$$

where $T\beta$ is the transient. T is a n by $2p$ matrix containing the known functional variables, $R_k^{-t} \cos \theta_k t$ and $R_k^{-t} \sin \theta_k t$, where R_k and θ_k are the radius and the angle respectively of the p complex roots in the AR polynomial. β is a $2p$ by 1 vector containing the parameters A_k and B_k that depend on the difference between the true and the assumed starting values. Thus we can write:

$$Y^0 = T\beta + Y \quad (2)$$

where Y^0 is the input series filtered with assumed starting values and Y is the true filtered series.

The unknown vector β can be estimated by a regression for which the error term Y , is considered to be the true filtered series. The estimator must take account of the fact that Y is autocorrelated. Rhoades suggests two estimation techniques. We used one of them, the generalized least squares approach (GLS). This requires a priori information about the auto-correlation function of Y . This can be obtained from the estimated auto-correlation of X_t and the filter. This implies that X_t must be stationary. Stationarity can be obtained by differencing the data. Long movements remain in the differenced data but with very low amplitude. They are retained by the filtering procedure. The original amplitude of the remaining cycles in the filtered series can be re-established by reversing the difference operator. First differencing in this case is not subject to the criticisms of the first differencing technique mentioned earlier because, after filtering, the first difference operator is reversed.

The problem of second order non-stationarity or increasing variance, can be practically solved by taking the appropriate Box-Cox transformation Yeo [1978] before differencing.

3.3 The Case of Bi-directional Filtering

Uni-directional filtering implies a phase shift of the cycles in the filtered series relative to their position in the input series. Bi-directional filtering avoids such a problem. The bi-directional filter is defined as:

$$\sum_{i=0}^m b_i Z_{t+i} = \sum_{j=0}^c a_j Y_{t+j}$$

where Y_t is the uni-directionally filtered series from equation (1) and Z_t is the bi-directionally filtered series.

In other words, the bi-directionally filtered series, Z_t , results from the uni-directional filtering of Y_t in the opposite direction, keeping in mind that Y_t results from the uni-directional filtering of X_t . Thus, for bi-directional filtering, the methodology requires that we assume two sets of starting values, one for Y_t and one for Z_t . The assumption of incorrect starting values will generate a transient ($9T.y$) that has a functional form defined to be:

$$\begin{aligned} 9T.y = & \sum_{k=1}^p A_k R_k^{-t1} \cos \theta_k t1 + B_k R_k^{-t1} \sin \theta_k t1 \\ & + C_k R_k^{-t} \cos \theta_k t + D_k R_k^{-t} \sin \theta_k t \end{aligned}$$

where BT is a n by $4p$ matrix containing the known functional variables,

$$R_k^{-t} \cos \theta_k t, R_k^{-t} \sin \theta_k t, R_k^{-t1} \cos \theta_k t, R_k^{-t1} \sin \theta_k t1 \quad (t1=n-t+1).$$

γ is a $4p$ by 1 vector containing the parameters A_k, B_k, C_k, D_k that depend on the difference between the correct and the assumed starting values. For bi-directional filtering, the equivalent of equation (2) is therefore:

$$Z^0 = BT.\gamma + Z \quad (3)$$

where Z^0 , the dependent variable, is the series X_t now filtered bi-directionally with assumed starting values and Z , the error term, is the correct bi-directionally filtered series.

Because Z_t has no phase shift distortion, we can specify equation (3) in terms of the difference between the input series, X_t , and the bi-directionally filtered series, Z_t , as the following regression equation:

$$X - Z^0 = -BT.\gamma + X - Z \quad (4)$$

where the dependent variable is now the difference between X and Z^0 ; the independent variable is BT ; and the parameters to be estimated are contained in γ . The error term is $X - Z$; the difference between the input series and the true bi-directionally filtered series. The GLS estimator is used to take account of any autocorrelation in $X - Z$. Information about the autocorrelation function for $X - Z$ can be derived from the autocorrelation of X_t, Y_t and Z_t .

3.3 Trend Discontinuity and Outliers

The spectral definition of the trend assumes that the secular movements in the economy are a juxtaposition of long cyclical waves. If the true trend has a break in it, or a discontinuity, this assumption is not valid. As yet there is no general solution to this problem; but we would argue that secular movements in the economy result from factors such as population, technology, etc. that do not change course quickly.

However, major wars can significantly influence economic evolution in a particular country. This temporary shift in the economy causes serious problems for filtering and identifying cycles. First, these events viewed as outliers add a transient to the filtered series. Second, outliers can seriously distort the estimates of the autocorrelation function used in GLS. Third, the spectrum estimates are biased.

The first problem is solved by estimating the transient related to the outliers in the same way as we did for the starting value problem. This requires the autocorrelation of X_t without the influence of certain observations, the outliers. Such an estimator was developed by Marshall [1980]. This solves the third problem as well because the spectrum is a numerical transformation (the Fourier transform) of the autocorrelation function.¹

¹A more comprehensive description of the outliers' solution can be found in Gervais [1986].

To summarize, simple modifications can be made to Rhoades' filtering method to ensure that outliers do not cause distortions. This set of specifications can allow one to detrend the data without altering the Kondratieffs. The spectral analysis of the detrended data then can be performed to verify their existence.

4. OUR INVESTIGATION

4.1 The Methodology

The three main statistical problems related to testing the long-wave hypothesis as outlined in section 2 will be dealt with as follows:

- a) Detrending is done using Rhoades' filtering method. The ARMA filter FTREND implemented by equation (4), estimates the trend. The amplitude distortion of the first difference filter and of FTREND are given in Table 3 (see also Figures 1 and 2). It is important to note that at the periodicities which correspond roughly to the Kondratieff cycle (say 50 years), the amplitude distortion of the first difference filter is substantial compared to that of the deviation from trend defined by FTREND.¹
- b) The second order stationarization of the detrended series is achieved by taking the proper Box-Cox transformation of the raw series before filtering. Yeo's method [1978] showed that the logarithmic transformation was the best for our data set. The stationarized series is therefore the logarithm of the raw series minus the logarithm of the estimated trend.

¹See also the discussion on page 7.

- c) The analysis of the periodogram is used to determine whether the long wave is a dominant cycle in the stationarized series. The periodogram is computed at the Fourier frequencies (the natural grid) to apply the q-test¹... a statistical test that determines the significance of dominant peaks in the periodogram. We also analyze the periodogram computed on a finer grid² (the padded grid) because the natural grid provides too few estimates at Kondratieff-related frequencies.
- d) Additional to the above points, the problem of wars is addressed by using Rhoades' filtering method modified for outliers. Table 2 gives the dates that were considered as outliers.

The interesting advantage of the filtering approach is that cycles can be isolated. We can therefore study the historical behaviour and dating of the Kondratieff cycle. We designed a filter, FKOND, that eliminates only fluctuations of about 35 years and less (see Table 3). The series resulting from the application of FKOND will be called Kondratieff trend; those resulting from the application of FTREND will be called secular trend. The difference between the Kondratieff trend and the secular trend is composed mostly of cycles from 35 to 100 years as shown by the last column of Table 3. The Kondratieffs should dominate this range of cycles.

¹See Priestley [1981:406-415].

²This is done in our study by adding zeros to the data before computing the periodogram. It should be noted that a test analogous to the q-test for the natural grid was not performed to determine the statistical significance of the dominant peaks in the periodogram related to the padded grid.

TABLE 2
THE DATA (IN REAL TERMS)

VARIABLES	SOURCE REFERENCE	RANGE	OUTLIERS
World energy consumption	Haustein and Neuwirth [1982]	1860-1978	None
Kuczynski's world industrial production	Haustein and Neuwirth [1982]	1850-1976	1940-1947
Haustein's world industrial production ^{a)}	Haustein and Neuwirth [1982]	1740-1983	1940-1947
Great Britain's industrial production ^{b) c)}	van Ewijk [1982]	1750-1984	1914-1924 1940-1947
France's industrial production ^{b) c)}	van Ewijk [1982]	1815-1983	1914-1924 1940-1947
Belgium's industrial production ^{b)}	Bossier and Hugé [1981]	1840-1984	1914-1924 1940-1947
Great Britain's GNP ^{b)}	van Ewijk [1982]	1830-1983	1914-1924 1940-1947
United States' GNP ^{b)}	van Ewijk [1982]	1789-1983	1940-1947

a) updated with U.N. statistics.

b) updated with the O.C.D.E. database.

c) these series were also used by van Duijn [1983].

TABLE 3
THE AMPLITUDE DISTORTION OF SELECTED FILTERS

FREQUENCY	PERIODICITY (in years)	FIRST DIFFERENCING ^{a)}	FTREND ^{b)}		FTREND ^{b)}		FKOND ^{b)}	CKOND ^{c)}
			DEVIATIONS	TREND	TREND	TREND		
.000	INFINITY	0.00	0.00	1.00	1.00	1.00	.94	(.06)
.001	1000	0.01	0.00	1.00	1.00	1.00	.94	(.06)
.002	500	0.01	0.00	1.00	1.00	1.00	.95	(.05)
.005	200	0.03	0.18	.82	1.00	1.00	.96	.14
.007	150	0.04	0.44	.56	0.89	0.89	.97	.41
.008	120	0.05	0.67	.33	0.62	0.62	.98	.65
.010	100	0.06	0.81	.19	0.30	0.30	.98	.79
.011	90	0.07	0.87	.13	0.15	0.15	.99	.86
.012	80	0.08	0.91	.09	0.05	0.05	1.00	.91
.014	70	0.09	0.95	.05	0.01	0.01	1.00	.95
.017	60	0.10	0.97	.03	0.00	0.00	1.00	.97
.018	55	0.11	0.99	.01	0.00	0.00	1.00	.99
.020	50	0.13	0.99	.01	0.00	0.00	.98	.97
.022	45	0.14	1.00	.00	0.00	0.00	.94	.94
.025	40	0.16	1.00	.00	0.00	0.00	.87	.87
.029	35	0.18	1.00	.00	0.00	0.00	.75	.75
.033	30	0.21	1.00	.00	0.00	0.00	.56	.56
.040	25	0.25	1.00	.00	0.00	0.00	.34	.34
.050	20	0.31	1.00	.00	0.00	0.00	.16	.16
.067	15	0.42	1.00	.00	0.00	0.00	.05	.05
.100	10	0.62	1.00	.00	0.00	0.00	.01	.01
.200	5	1.18	1.00	.00	0.00	0.00	.00	.00
.500	2	2.00	1.00	.00	0.00	0.00	.00	.00

a) Amplitude distortion of the first difference filter.

b) Amplitude distortion of the filter applied bi-directionally.

c) Amplitude distortion of FKOND-FTREND.

4.2 The Data

We have chosen data that permit testing of the long-wave hypothesis at the macro-economic level. There might well be such a cycle in sub-aggregate variables but if the Kondratieffs are confined to these variables, they cannot be labelled as a characterization of general economic development.

Table 2 gives some information about the series we used. All of them have been tested in other studies. This permits us to compare our results to others.

4.3 The Results

The periodogram analysis results are summarized in Table 4. For 7 of the 8 series, the padded grid periodogram indicates spectral peaks at frequencies which correspond to periodicity of 51 to 64 years. Six out of those 7 spectral peaks remained in the Kondratieff frequency range when the natural grid was used rather than the padded grid and are significant at the 1% level according to the q-test.

Turning to the results in more detail, Figures 6a to 6e give additional information on the analysis of Kuczynski's index of world industrial production. Figure 6a shows the log of the raw series with replacement values for the Second World War (dotted line), the log of the secular trend (cycles of over 100 years - continuous line) and the log of the Kondratieff trend (cycles greater than 35 years - dashed line). In Figure 6b, the dotted line, represents the difference of the log of the raw

TABLE 4
PERIODOGRAM ANALYSIS RESULTS

VARIABLES	FTREND	
	PADDED GRID PEAKS (in years)	NATURAL GRID PEAKS (in years)
World energy consumption	64	59.5*
Kuczynski's world industrial production	64	63.5*
Haustein's world industrial production	128, 73 and 57 ^a)	81*
Great Britain's industrial production	129 and 51	118*
France's industrial production	51	56*
Belgium's industrial production	85 and 51	49*
Great Britain's GNP	85	77*
United States' GNP	64	65*

VARIABLES	FTREND1	
	PADDED GRID PEAKS	NATURAL GRID PEAKS
Haustein's world industrial production	85 and 51 ^a)	61*
Great Britain's industrial production	51	59*
Great Britain's GNP	51	51*

*Significant at the 1% level.

^a) Among those three peaks the one corresponding to a periodicity of 57 years was the highest.

data and the log of the secular trend. The continuous line in this figure represents the difference of the log of the Kondratieff trend and the log of the secular trend and shows that the Kondratieff cycle is dominant and follows the expected historical pattern. Figures 6c and 6d graph the spectral estimates for the padded and the natural grids respectively. Figure 6e shows the annual percentage rate of growth for the secular trend and the Kondratieff trend. While there is much interesting information contained in the filtered series for anyone studying long-term economic development, its analysis (see Gervais, 1986) goes beyond the present paper.

Turning to industrial production for Great Britain, the application of the filter FTREND and the natural grid produced a significant spectral peak at 118 years. However, the natural grid may have too few observations to identify the Kondratieff cycle because the results based on the same filter and the padded grid indicate two distinct dominant cycles at 128 and 51 years respectively. The objective in designing a new filter (FTREND1) was to eliminate the influence of the 128-year cycle. Applying the new filter produced a significant peak of 59 years on a natural grid basis and a dominant peak of 51 years on a padded grid basis.

FTREND1 was also applied for the same reasons to Haustein's index of world industrial production. The periodogram results using FTREND1 and the natural grid show a significant spectral peak at 61 years. The padded grid periodogram using FTREND1 suggests that there are 85- and 57-year cycles. These results may mean that the Kondratieffs are not well-defined dominant cycles. The analysis of the filtered series suggests that these spectral

Figure 6A

- 24a -

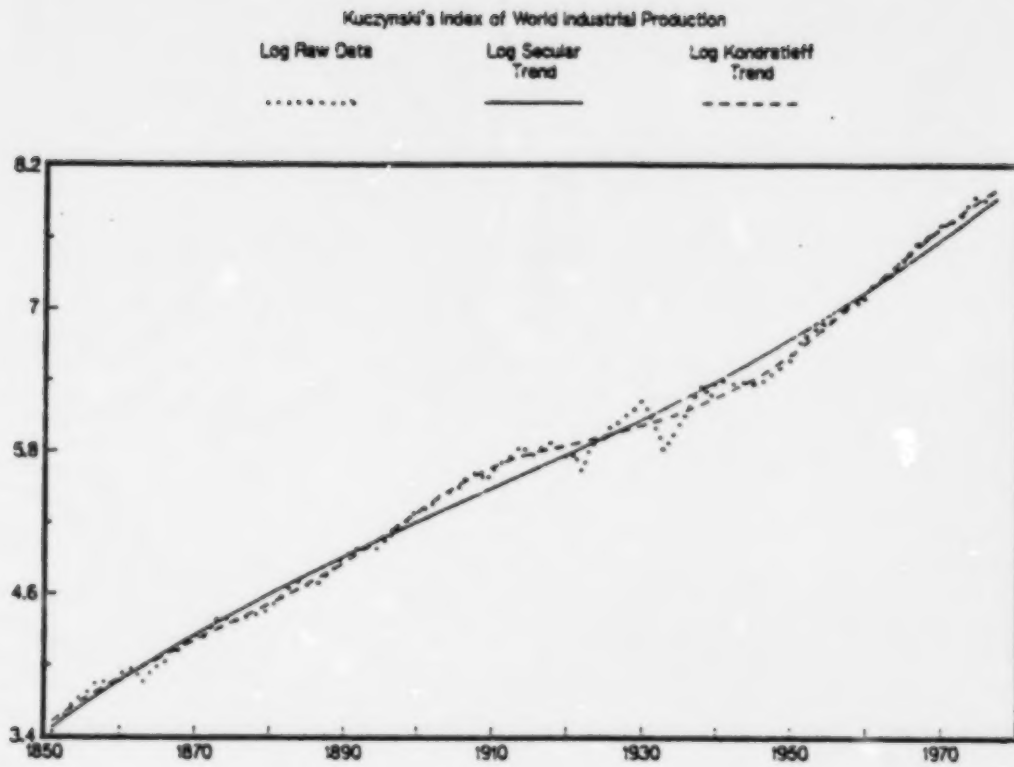


Figure 6B

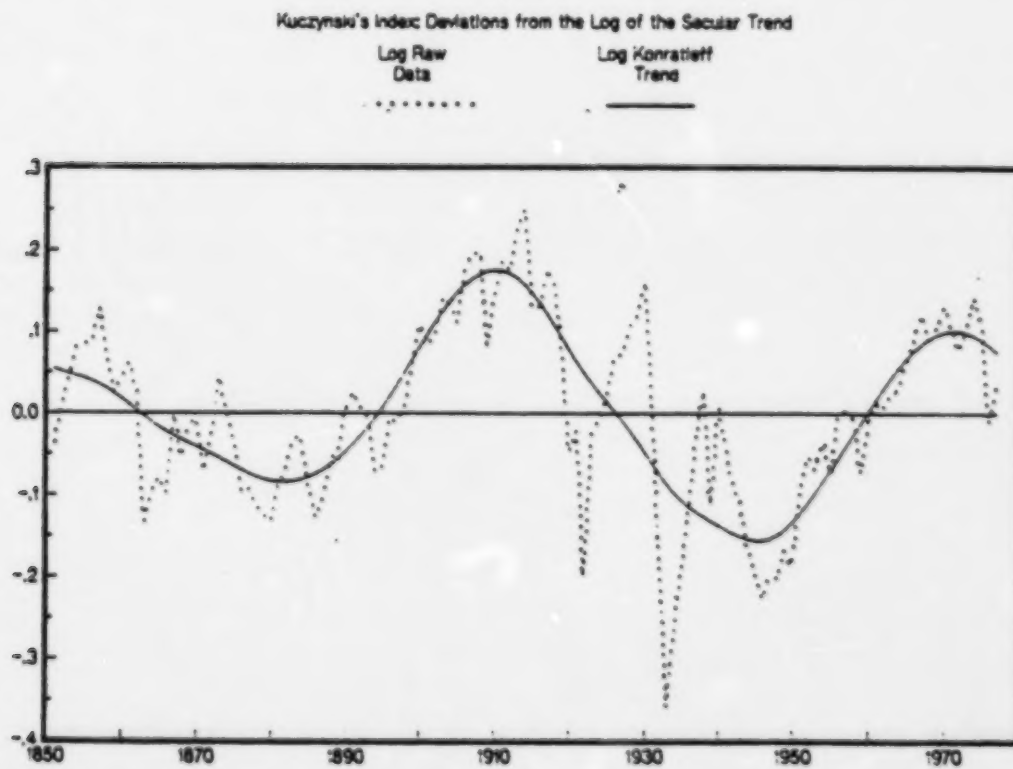


Figure 6C

- 24b -

Padded grid periodogram for Kuczynski's Index

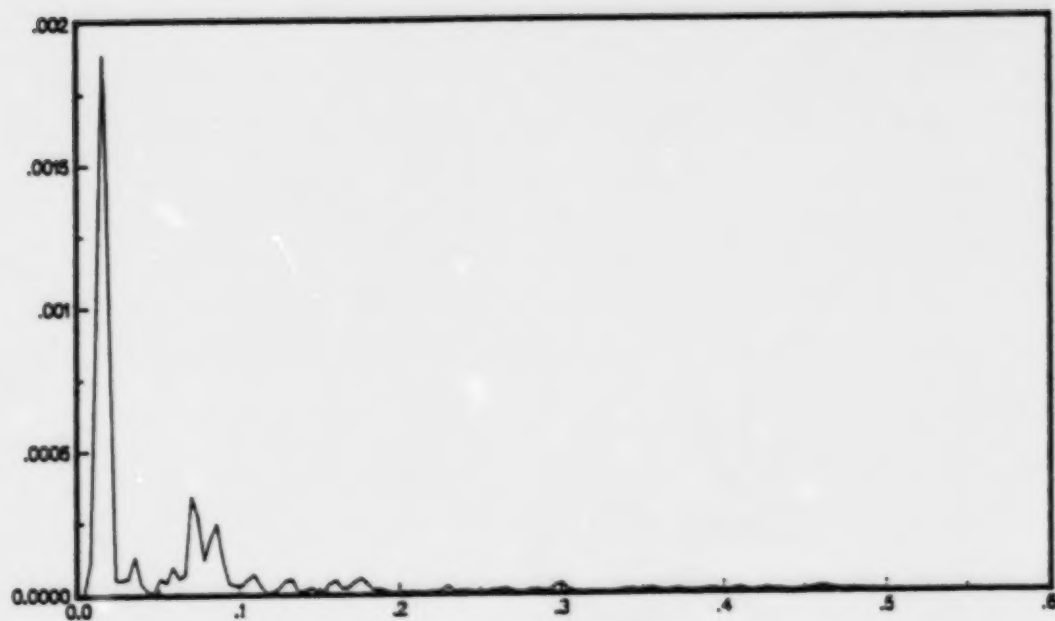


Figure 6D

Natural grid periodogram for Kuczynski's Index

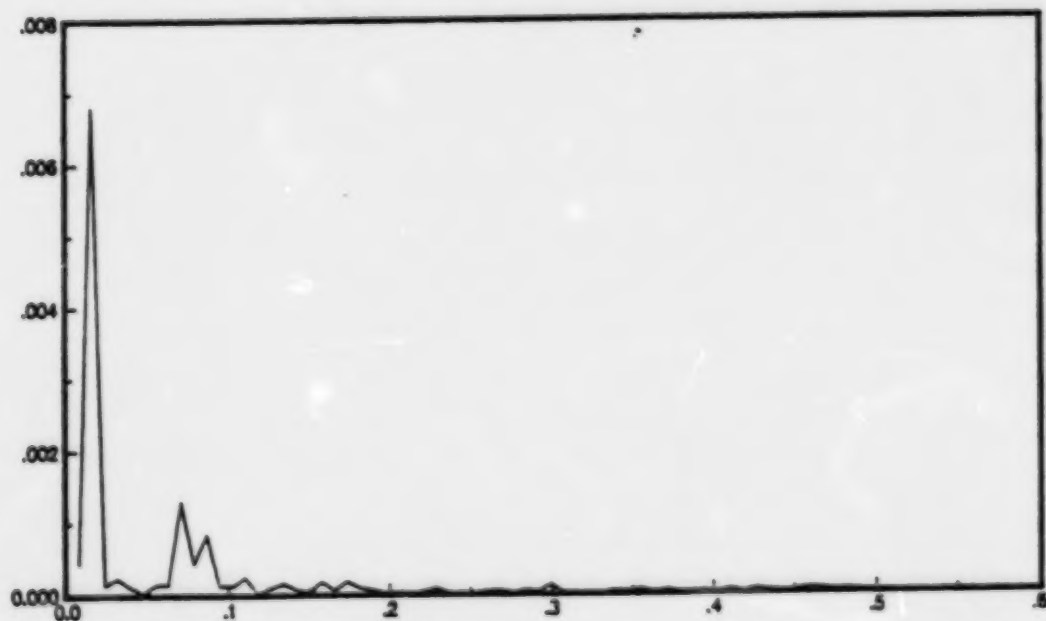
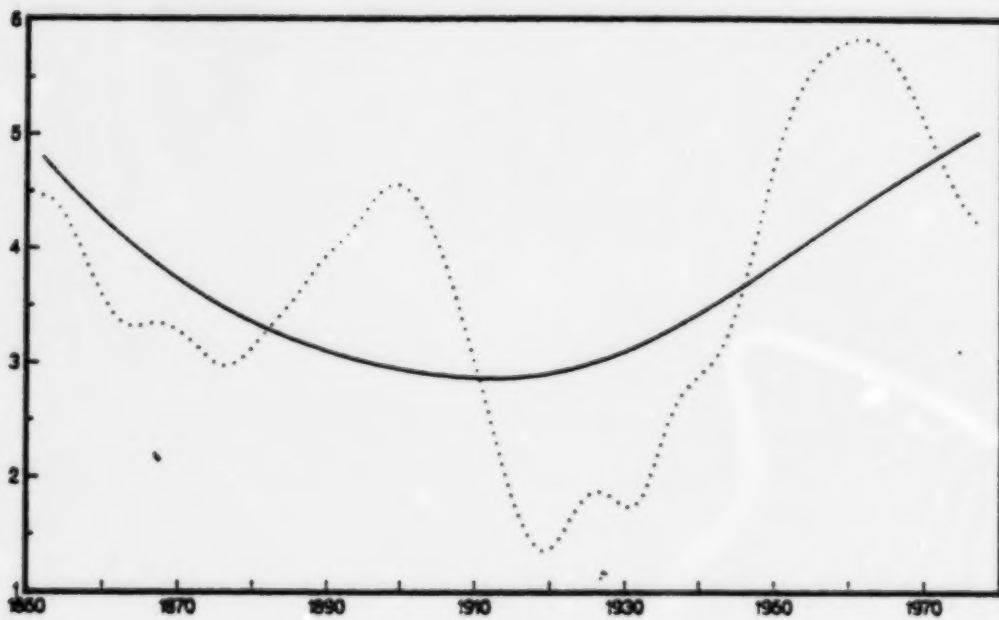


Figure 6E

Kuczynski's Index Percentage Annual Growth Rates

Kondratieff
Trend

Secular
Trend



results are attributed to only one poorly defined Kondratieff cycle. The dotted line in Figure 7a shows the difference between the log of Haustein's actual data and the log of the trend defined by FTREND1. The continuous curve represents the isolated Kondratieff cycles. The Kondratieff wave from 1825 to 1881 has a very low amplitude so that the 19th century is dominated more by a one hundred-year cycle. It is worth noting that Haustein's index is a combination of Great Britain's index of industrial production up to 1850 and then Kuczinsky's world index updated with United Nations statistics. The low amplitude Kondratieff at the link suggests that there might be a trend discontinuity between those series. The annual percentage rate of growth for the secular trend (FTREND1 - dotted line) and the Kondratieff trend (continuous line) defined for Haustein's data is illustrated in Figure 7b and supports the idea of discontinuity.

The only series for which the periodogram analysis based on FTREND did not exhibit spectral peaks at Kondratieff frequencies is Gross National Product for Great Britain. For these series and filter, the amplitude of the cycles at the Kondratieff frequencies is high relative to that of the shorter cycles but not to that of the longer ones. In other words, the Kondratieffs may exist but they are not dominant relative to longer cycles. However, the long-wave cycle becomes dominant and significant according to the g-test if one uses FTREND1. FTREND1 dampens those long movements enough to render the Kondratieffs dominant.

Figure 7A

- 25a -

Hausman's Index Deviations from the Log of the Secular Trend

Log Kondratieff
Trend

Log Raw Data

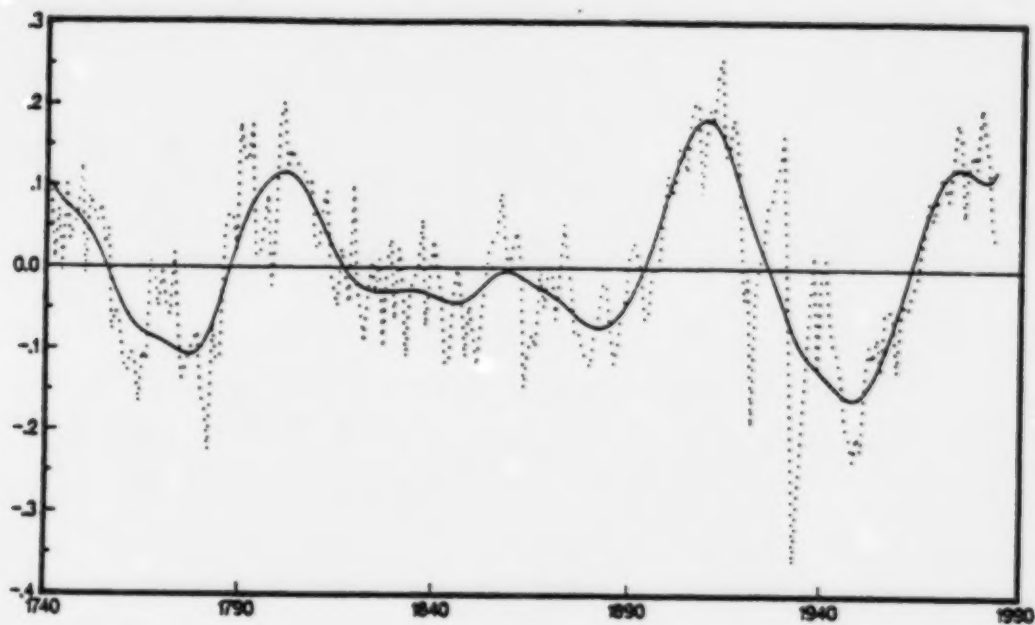
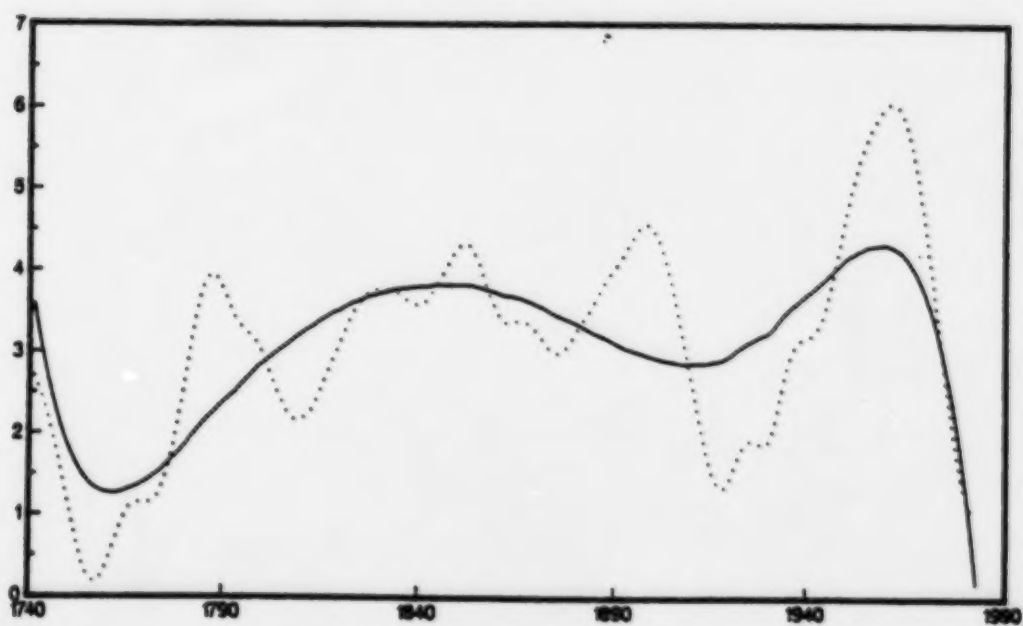


Figure 7B

Hausman's Index Percentage Annual Growth Rates

Kondratieff
Trend

Secular Trend



5. CONCLUSION

To summarize, our investigation accepts the Kondratieff long-wave cycle hypothesis in a statistical sense for macro-economic variables in industrialized countries. The q-test suggests that the Kondratieff spectral peaks are not due to randomness based on the sample properties of the periodogram estimates. However, these results do not mean that the causes are endogenous to the system and that it will repeat itself in the future. These fluctuations could have been caused by exogenous historical events that happened half a century apart. The statistical test results would have been the same as if these events were endogenous.

Thus, the most important questions remain to be answered. What did in fact cause the observed long-wave cycle? Is the present low growth rate of the world economies attributed to the internal dynamics of the economic system? Our belief is that Rhoades' filtering method can help answer those questions as it permits us to isolate and therefore better study long-term economic movements and business cycles.

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